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MULTIOBJECTIVE FUNCTIONS OPTIMIZATION FOR TASK ALLOCATION MAPPING TO MULTICOMPUTER NODES

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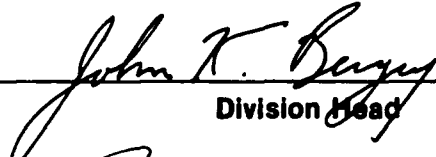JUL 2 2 1993
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13. ABSTRACT (Maximum 200 words)

The Naval Air Warfare Center - Aircraft Division Warminster, Software & Computer Technology Division, is developing software to allocate tasks to multicomputer nodes such that multiple objectives are optimized. The eventual goal of this project is to allow the decision maker to have design optimization capabilities available to her/him when designing complex systems.

Two key aspects of the allocation problem are discussed: 1. The techniques used to treat multiple objectives simultaneously and 2. The techniques used to perform the search for the optimal set of model parameters.

The report discusses current research reported in the literature and makes several suggestions for continuing the current effort. The current technique being used for treating multiple objectives simultaneously is to use a weighted sum of each of the individual objective functions as the objective function for the search. It is suggested that a vector of objective functions approach be implemented and experimentally compared to the weighted sum approach. Two algorithms are being

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used in the software: the genetic algorithm and the simulated annealing algorithm. It is suggested that a neural network search technique be added as a third alternative with experiments to determine regions of superiority of the different search techniques.

14. SUBJECT TERMS (Continued)

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. Multiobjective Functions Optimization

Introduction

At the present time the Naval Air Warfare Center (NAWC), Aircraft Division, Warminister, Software & Computer Technology Division (SCTD), is developing software to solve the problem of multiple objective task allocation to multicomputer nodes optimally. This type of optimization problem is classified as an NP-complete problem of exponential time complexity. Two algorithms are being used in the software: the genetic algorithm and the simulated annealing algorithm. The eventual goal of this project is to allow the decision maker (DM) to have options available to her/him when designing networks of allocating linked software tasks to linked computer hardware nodes.

In terms of modeling the problem, the approach is to create one objective function from a weighted sum of all the individual objective functions. SCTD is using task precedence graphs to model the problem rather than using a task interaction graph mapping. This problem can be classified as a combinatorial optimization problem concerned with finding the *best* or optimal solution among a finite or countably infinite number of alternative solutions (Sheddin).

The language implementation is in Ada, using a linked list structure.

Literature Search

A search of the literature reveals that abundant research is in progress with respect to the use of the genetic algorithms and simulated annealing algorithms in the solving of optimization problems. Another technique is also gaining much attention and that technique is the use of artificial neural networks to solve optimization problems.

Fox and Furmanski (1988) developed a "bold neural network" algorithm for balancing the load for mapping loosely synchronous problems onto hypercubes. Neural networks had been used by Hopfield and Tank (1986) for the solution of optimization problems such as the traveling salesman (TSP). Their work showed that neural networks are fast, reliable, and easy to implement.

Mansour and Fox (1991) have done experiments involving the use of genetic (GA), simulated annealing (SA), and neural network (NN) algorithms applied to different problem sets. The problem sets involve allocating data to multicomputer nodes. These experiments have compared the three algorithms with respect to solution quality, execution time, bias, parallelizability, and robustness. Their results indicated that the genetic and simulated annealing algorithms give good solutions that are close to optimal but the algorithms are very slow for problems of moderate size. However, the neural network algorithm does not give as good a solution as the genetic or simulated annealing algorithms but the algorithm is much faster than the other two algorithms. The neural network algorithm also tended to favor certain types of topologies. They use an approximate objective function that is smooth and consists of a weighted sum of individual objectives. This approximate objective function overcomes the non-smooth objective function that applies to the problem. The two goals of the optimization are load balancing and minimum communication. Their implementation language is FORTRAN.

Mansour and Fox (1992) evolve these three algorithms (GA, SA, and NN) into parallel versions. The parallel versions of these algorithms are applied to allocating irregular or general data to multicomputer nodes such that total execution time is minimized. The data allocation problem is an NP-complete resource allocation problem. The parallization of the algorithms is needed for large or dynamically varying problems. This effort was part of a larger FORTRAN D project.

Multiobjective Functions Optimization

The three parallel algorithms were compared for solution quality, bias, execution time, scalability, robustness, and memory space requirements. Comparisons of the three parallel algorithms consistly showed the genetic version producing the best solutions, with simulated annealing second best, and neural network solutions last. With respect to execution time the genetic version is the slowest and the neural network version is the fastest.

The parallel algorithms were less robust than their sequential counterparts.

For large problems the genetic version required large memory space. The authors indicate that this problem of large memory space requirement could be overcome by adding a preprocessing graph contraction step to the algorithm. This might lead to a decrease in solution quality, but it would lead to a significant decrease in execution time.

The parallel versions of simulated annealing and neural networks are scalable. The genetic version could be scalable, also, if the above suggestion of circumventing memory space restriction was implemented.

At NAWC, the Air Vehicles and Crew Systems Technology Department, Steinberg and DiGirolamo (1991) are using neural networks to develop flight control systems with a goal to prove that neural network based approaches are feasible in meeting flight safety requirements for implementation on manned aircraft. They are using neural networks to resolve the complex design of flight control systems (FCS) and to create designs with better performance for less labor and cost. Their implementation languages are FORTRAN and C++. They do not use Ada in their work.

Freeman and Skapura (1991), working with neural networks, recommend the use of network data arranged in groups of linearly sequential arrays, since it is much faster to step through an array sequentially than it is to look up the address of every new value as would be done if a linked-list approach were used. They give several examples using pseudo-code and data structure diagrams.

Multi-objective Functions

The discussion so far has concentrated on the algorithms to use to solve task allocation problems. We now turn to the problem of more than one objective to optimize, or the optimization of multiple objectives. Wann et al (1992) have taken the approach of optimizing a weighted sum of the individual objective functions. Warburton (1987), working with methods for approximating the set of Pareto optima paths in multiple objective, shortest-path problems, cautions that using a weighted linear combination of objective functions to approximate the optimal may miss large sections of efficient sets of acceptable solutions and we do not know which sections are unknown. Pareto optimality is the set of efficient answers that are not dominated by others. Cohen (1992) (referring to Warburton) and Warburton (1987)suggest using a vector of objective functions approach to the optimization problem. The approximation methods are fully polynomial.

Paul (1990) worked on the problem of assigning naval officers to certain billets using a hierarchy of multiple objectives. His problem was the classical 0-1 assignment problem. His technique for solving this problem was to create a hierarchy of the objectives and solve various subproblems using the objectives eventually as constraints in the subproblems. The first subproblem is solved using the highest priority objective function only. The second subproblem is solved using the second highest priority objective function, but with the first highest objective function now used as a constraint (or a high percentage of it). Continue in this manner for each additional objective function with each higher

objective function used as one of the constraints. The process is finished when all objective functions have been exhausted. He used the simulated annealing algorithm and obtained reasonable results on problems with small search spaces.

Ercal (1988) addressed the problem of static task mapping and used task interaction graphs to model the mapping of iterative parallel programs onto processors. His problem involved two goals: 1) even distribution of total computational load among the processors, and 2) minimization of interprocessor communication. He used two differeit approaches for comparison: graph-based heuristic approaches (nearest-neighbor approach and mincut-based clustering schemes) and modified simulated annealing. Comparisons were also made with a greedy algorithm. The results of his work indicated that the modified simulated annealing algorithm, with regard to solution quality and running time fell in between graph-based heuristic approach and the greedy method.

Bollinger and Midkiff (1988) worked on the problem of mapping a set of processes and their communication requirements onto a multicomputer. They did not consider the problem in which the number of processes exceeds the number of processors. The multiple objectives of load balance and minimizing interprocessor communication traffic over network links were combined into one objective using a weighted sum of the individual objectives. A weight was attached to one objective such that that objective would be heavily penalized if it increased during the optimality process.

Zoints and Wallenius (1976) used an interactive mathematical programming method for solving the multiple criteria problem involving a single decision maker. The basis of their method is the feasibility of using linear approximations to represent the set of constraints and objective functions. Their method was to create a composite objective function (or utility function) using multipliers (weights). The composite objective function was optimized to produce an efficient or Pareto-optimal solution to the problem. An example (profits of a firm), in which the utility function is not linear, is given with the objective modified to retain the assumption of linearity.

In their model the sum of the weights is one. The weights are chosen such that it is not possible to increase (decrease) one objective without decreasing (increasing) at least one other objective function.

Loganathan and Sherali (1987) discussed different classifications of the multiobjective optimization problem. The first type has the task of characterizing the set of efficient, or nondominated, or Pareto optimal, solutions. These solutions are such that no other solution can improve even one objective function without worsening the others. The task of selecting among such solutions is typically left unaddressed. Here the knowledge of the decision maker is not used.

At the other extreme the decision maker's preferences are specified as in goal programming or multiattribute utility theory. Since the decision maker's utility function is explicitly known, the problem is not a *true* multiobjective program, since it may be solved as a single scalar problem.

A third approach, and intermediate type of approach, is one that uses partial progressively revealed information regarding the decision maker's preferences. This approach is known as an interactive method because it seeks information progressively from the decision maker. These methods typically seek to solve a sequence of subproblems.

Definitions

Goldberg (1989) defines the genetic algorithm as a search algorithm based on the mechanics of natural selection and natural genetics.

Freeman and Skapura (1991) define neural networks (also known as connection networks) as a collection of *parallel processors* connected together in the form of a directed graph, organized such that the network structure lends itself to the problem being considered.

Shedden:(1990) defines simulated annealing as a general purpose approximation algorithm applicable to many combinatorial optimization problems. The algorithm behaves like a local serach that probabilistically accepts transitions away from a optimality, thus allowing it to escape local optima in its search for the global optimum. This algorithm is independent of initial configurations.

The combinatorial optimation problem is concerned with finding the *best* or optimal solution among a finite or countably infinite number of alternative solutions.

Chen (1990) states that simulated annealing is derived from Monte Carlo methods in statistical mechanics and is a stochastic optimization algorithm that simulates the annealing process. The algorithm was first utilized as a simulation method to examine the properties of substances consisting of interacting individual molecules. The purpose of the simulation is to find the ground states of a system which corresponds to the configurations of low energy molecular structure.

Simulated annealing has a goal of finding the minimum of a function of many variables by first *heating* the system being optimized at a high temperature and then lowering the temperature in slow stages until the system *freezes* The sequence of temperatures, including the melting point and freezing point, is called the annealing schedule.

Blower (1990) says that simulated annealing has a goal of finding the minimum of a function of many variables by first *heating* the system being optimized at a high temperature and then lowering the temperature in slow stages until the system *freezes* The sequence of temperatures, including the melting point and freezing point, is called the annealing schedule.

Simulated annealing is a stochastic-search technique with a control parameter represented by the temperature. The algorithm attempts to evaluate a complicated multidimensional integral by Monte Carlo sampling approach. The Monte Carlo technique is necessary because the integral is too complicated to solve through conventional analytical means. Because of the complicated nature of the integral, the Monte Carlo approach follows a scheme designed to provide better sampling of the states where major contributions to the integral are made.

Simulated annealing was very time consuming, and its performance on this highly simplified problem should not be construed as ablanket recommendation when scaling up to the real world.

Relationship between statistical mechanics and combinatorial optimization.

Statistical Mechanics	Combinatorial Optimization
States (of system)	Solutions (to problem)
Energy (of states)	Cost (of solution)
Ground State	Optimal Solution

. Multiobjective Functions Optimization

Suggested Approaches

SCTD should add a neural network algorithm to their set of algorithms which already contains genetic and simulated annealing algorithms. In order to give the user or decision maker an idea of which of these algorithms might be most suitable to meet her/his needs in the design process experiments should be performed similar to those done by Mansour and Fox (1991). Performance criteria should be solution quality, execution time, robustness, bias, and parallelizability. Performances should be critically evaluated and compared for a number of examples with different topologies, sizes, and granularities. Following the Mansour and Fox (1992) lead additional algorithms, the parallel versions of the present three algorithms, should be added to the repertoire and once again experiments for critical evaluation and comparison should be made. Once these experiments and their results are known it will be easier to advise the user as to which algorithm to use for a particular design problem. M. Wann is recognized as a neural networks expert at NAWC and the implementation of a neural nets algorithm should present no difficulty.

Additional experiments should be performed with a new model to the design problem where the individual objective functions are represented as a vector of objective functions. These result should be compared to the weighted sum results to see if better solutions can be obtained.

If the Mansour and Fox (1991) results are confirmed, i. e., neural networks are much faster than the genetic and simulated annealing algorithms, but solutions are not as good, then one should consider a situation where the user applies the neural network to an optimization problem and then takes that solution and uses it as input (starting point) for applying the simulated annealing algorithm. This is the idea of the Boltzmann machine or the Cauchy machine (Freeman and Skapura). Speedups and solution quality of this hybridization might be of interest to the user. Freeman and Skapura (1991) suggest the possibility of using classical optimizing techniques once near a minimum. This could be presented to the DM as an option.

Others are using FORTRAN for implementation of these algorithms (neural network, genetic, and simulated annealing algorithms and their parallel versions.) Steinberg and Digirolamo do not even consider using Ada as the language of implementation. SCTD is restricted to Ada. Would the tasking features of Ada improve the implementation process for these design problems?

Although Ada is designed to allow 30 tasks concurrently, actual experiments have shown a maximum of 10 to 11 tasks concurrently in reality. FORTRAN can be designed to run many more than 30 tasks concurrently. (1988 SIAM Conference on Parallel Computing, Denver, CO) This deficiency should be eliminated in Ada 9X.

The Wann et al paper does not specify how the weights for the composite objective function should be selected, or if there is any relationship between the weights. The best approach might be to have the weights sum to one. This would follow the approach of Pareto optimality where one objective cannot be improved without worsening at least one other objective.

The final product should contain pseudocode and data flow, or data structures diagrams. This would help with maintaining the code.

The simulated annealing and genetic algorithms do not appear to guarantee the avoidance of local minima. A suggestion here would be to enhance the code such that avoidance of local minima is guaranteed. The present algorithms do seem to be of a scalable nature. This would need to be taken care of if the project is to be expanded arbitrary topologies.

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